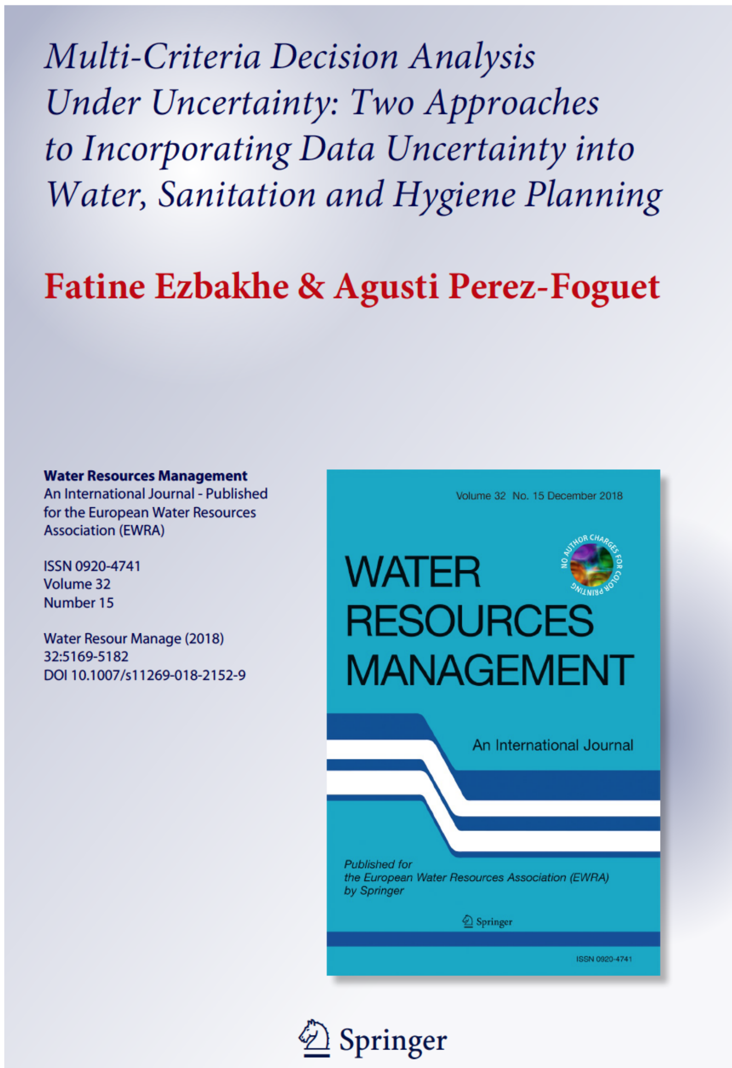
A revised version of this article has been published as: Ezbakhe, F., Perez-Foguet, A. 2018. Multi-Criteria Decision Analysis Under Uncertainty: Two Approaches to Incorporating Data Uncertainty into Water, Sanitation and Hygiene Planning. Water Resources Management 32(15) 5169-5182.http://dx.doi.org/10.1007/s11269-018-2152-9



Multi-Criteria Decision Analysis Under Uncertainty: Two Approaches to Incorporating Data Uncertainty into Water, Sanitation and Hygiene Planning

Fatine Ezbakhe[a], Agusti Perez-Foguet[a]

[a]*Research group on Engineering Sciences and Global Development, Department of Civil and Environmental Engineering, Barcelona School of Civil Engineering (ETSECCPB), Universitat Politcnica de Catalunya BarcelonaTech*

Abstract

In the era of the Sustainable Development Goals, where one of the aims is to provide universal access to safe Water, Sanitation and Hygiene (WASH) services, it is crucial to target and prioritize those who remain unserved. Multi-Criteria Decision Analysis (MCDA) models can play an important role in WASH planning by supporting priority-setting and policy-making. However, in order to avoid misleading assumptions and policy decisions, data uncertainty — intrinsic to the available collection methods — must be integrated in the decision analysis process. In this paper we present two approaches to incorporate data uncertainty into MCDA models (MAUT and ELECTRE-III). We use WASH planning in rural Kenya as a case study to illustrate and compare the two approaches. The comparison focuses on the way these two models handle the uncertainty in the available data. The analysis shows that, while both methods incorporate data uncertainty in a considerable different manner, they lead to similar prioritization settings.

Keywords:
Multi-criteria decision analysis, ELECTRE III, MAUT, Data uncertainty, Water, Sanitation and Hygiene

Email addresses: `fatine.ezbakhe@upc.edu` (Fatine Ezbakhe), `agusti.perez@upc.edu` (Agusti Perez-Foguet)

1. Introduction

Achieving universal access to safe water, sanitation and hygiene (WASH) services by 2030 is a huge endeavour for countries worldwide (UN-Water 2018). Targets 6.1 and 6.2 of the Sustainable Development Goals challenge governments to tackle the 'unfinished business' of extending WASH services to those who remain unserved, as well as progressively improve the level of services provided. The progressive realization of universal access to WASH and the reduction of inequalities in service levels is also consistent with the United Nations resolution on the human rights to water and sanitation (United Nations 2010). However, the commitment to 'leave no one behind' requires increased targeting and prioritization of those most in need of better WASH services. As the UN Special Rapporteur on the human right to safe drinking water and sanitation (2011) explains, governments must give "priority to realizing a basic level of service for everyone before improving service levels for those already served".

This requires, amongst others, WASH planning tools that target the neediest and support equity-oriented prioritization (Giné-Garriga et al. 2015). Evidence-based targeting and prioritization procedures do not only allow the identification of the segments and sectors of population in which to focus policies, but also guide a more equitable allocation of resources. Yet, decision-making processes in the WASH sector often lack transparency and accountability, and can lead to discrimination against certain population groups (Ibid.). A step forward to support targeting and prioritization is thus the establishment of appropriate decision-making tools that assist policymakers and implementers in revealing which population groups are the most in need of further WASH services.

Multi-Criteria Decision Analysis (MCDA) models can play an important role in informing WASH planning. MCDA is a quantitative decision analysis model that evaluates and compares alternative decision options (e.g. communities or administrative sub-units) in terms of their services on a set of criteria (e.g. service coverage, service levels, etc.). By ranking population groups against multiple planning criteria, MCDA models can provide insight on priority-setting and development of WASH interventions. A wide variety of MCDA models exist today, and can be grouped in two main approaches (Ishizaka and Nemery 2013): *(i)* value measurement models (or 'American school'), based on the construction of a numerical score for each alternative (e.g. Multi-Attribute Utility Theory, MAUT), and *(ii)* outranking models (or 'European school'), based on the pairwise comparison between the alternatives (e.g. ELimination and Choice Expressing REality, ELECTRE).

The differences between the two MCDA families are substantial. First, there is no underlying utility function in outranking models: the output is a ranking of alternatives without any scores to indicate the extent to which one alternative is preferred to another. Second, the set of decision rules describing the aggregation procedure in outranking models are only partially compensatory, which limits the trade-offs between the different criteria (Stewart and Losa 2003). Yet, despite these considerable differences, only a few studies have attempted to compare them and dive into their decision analysis procedures. Table 1 summarizes the most relevant studies in water resources management addressing this comparison.

What has not been done before is extending MCDA models to the context where the data feeding the analysis has a certain level of uncertainty. Data uncertainty — the degree to which data is inaccurate, imprecise or unknown — arises from various factors, such measurement errors, data staleness and repeated measurements (Tsang et al. 2011). In the WASH sector, data uncertainty is intrinsic to the available collection methods. Household surveys represent a crucial source of data, and have developed into standardized sampling techniques and harmonized questionnaire designs to produce comparable estimates across countries and over time (WHO and UNICEF 2006). However, data from household surveys is not extent from uncertainty. All survey point estimates have a certain level of error, regardless of the size or design of the sample. This is particularly important in decentralized contexts with small populations (e.g. fewer than 500 households), where the high level of disaggregation makes it indispensable to balance the precision of survey data against survey costs (Pérez-Foguet and Giné-Garriga 2018). In using the household survey data for WASH planning, policymakers and implementers must consider the underlying uncertainty in order to avoid decisions based on false or misleading assumptions (Giné-Garriga et al. 2013).

Against this background, we present two MCDA approaches, based on MAUT and ELECTRE-III, for integrating data uncertainty into the decision analysis process. Our aim is guided by three main research questions:

1. How can we adapt MAUT and ELECTRE-III models to incorporate the uncertainty of the input data during preference modelling?
2. In what manner can we characterize the uncertainty of the input data and quantify its effect on the resulting model's output?
3. How convergent or divergent are the results (i.e. rankings) of each model?

The contribution of this paper is twofold. First, to the best of our knowledge, this work is the first attempt to extend MAUT and ELECTRE-

III models to tackle data uncertainty in water decision-making. Second, the paper addresses the growing need in WASH sector for improved targeting and prioritization instruments. Although our motivation comes from the WASH sector, the two approaches we present can also be applied in other areas of water management coping with the issue of numerical inaccuracy in the data.

The remainder of the paper is structured as follows. An overview of MAUT and ELECTRE-III methods is presented in Section 2. Section 3 describes the case study of WASH planning in rural Kenya. In Section 4 we present and discuss our proposed MCDA models for incorporating data uncertainty (4.1), the characterization of uncertainty and the treatment of propagation of uncertainties (4.2) and the comparison between rankings (4.3). Final conclusions are drawn in Section 5.

2. MCDA methods

Both MCDA methods begin with the definition of the decision problem, composed by:

- A set of m alternatives, A: $A = \{a_1, a_2, ..., a_i, ..., a_m\}$
- A set of n criteria, C: $C = \{c_1, c_2, ..., c_j, ..., c_n\}$
- A set of n weights coefficient for the criteria, W: $W = \{w_1, w_2, ..., w_j, ..., w_n\}$
- The evaluation matrix, G, with the performance values of each alternative a_i on criterion c_j in row i and column j: $G[i, j] = g_j(a_i)$

The first of the two models derives from the Multi-Attribute Utility Theory. The model considers two steps:

- Aggregation: a utility function is defined to construct the global value of each alternative. Several possible functions (additive, multiplicative and multi-linear) can be used. In this paper, for simplicity reasons, we restrict our attention to the additive form: the utility value for each alternative, $U(a_i)$, is calculated as the sum of the weighted performance values for each criterion.
- Exploitation: the utility values obtained in the first step are used to rank the alternatives.

The second model is based on ELECTRE-III (Roy et al. 1992). It also consists of two steps:

- Outranking relation: the method starts by building a preference relation, known as 'outranking relation' $S(a_1, a_2)$, between each pair of alternatives. To do so, a series of pairwise comparisons of the alternatives is done using the concordance-discordance principles.

- Exploitation: the outranking relations obtained in the first step are used to build two pre-orders through descending and ascending distillations, Z_1 and Z_2. A final pre-order of the alternatives is suggested as the intersection of these two.

The construction of the concordance and discordance indexes for each pair of alternatives requires the definition of three discrimination thresholds for each criterion: indifference threshold (q_j), preference threshold (p_j) and veto threshold (v_j). Choosing these thresholds values can be, however, challenging for decision-makers, as it involves a high degree of subjectivity (Ezbakhe and Pérez-Foguet 2018)). Figure 1 illustrates a summary of the decision analysis procedures of both MCDA models.

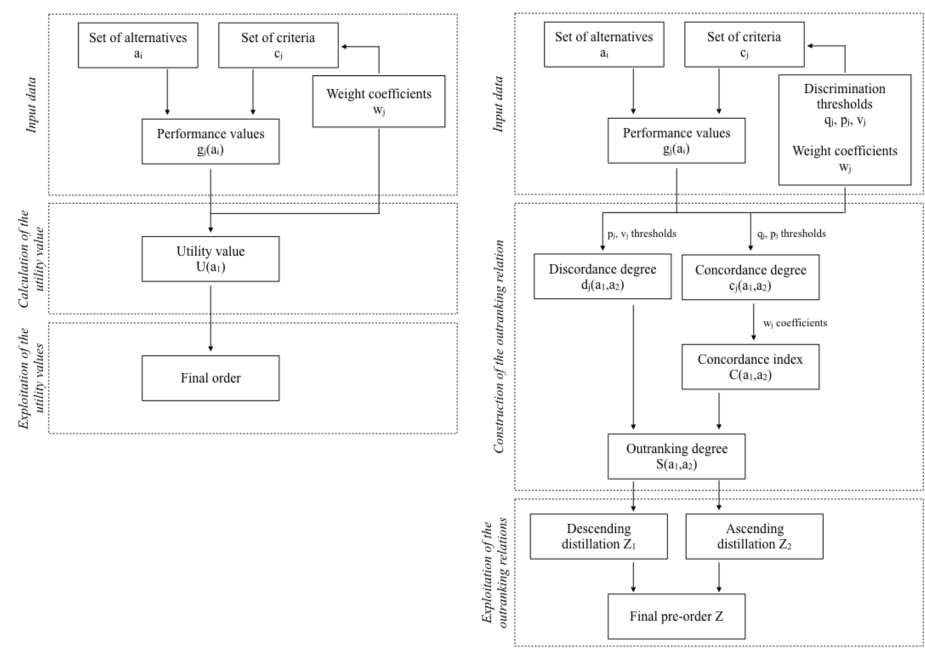


Figure 1: General decision analysis procedure of MAUT (left) and ELECTRE-III (right) models.

3. Case study

In rural Kenya, a large proportion of the population lacks access to safe WASH services. According to previous national official statistics, only half of the people living in rural areas used improved sources of drinking water and less than 20% had access to safe sanitation and hygiene facilities (Kenya National Bureau of Statistics 2010). In order to increase the access to appropriate WASH services, in 2010 the Kenyan Government in collaboration with UNICEF, launched an initiative to target the most vulnerable rural populations. This case study focuses on these rural areas, found in 21 districts across the country (Figure 2).

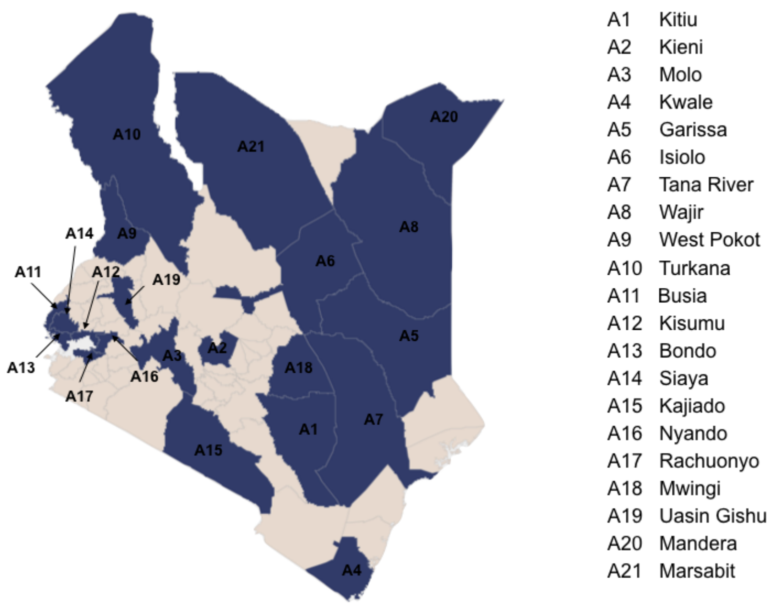


Figure 2: Map of Kenya with WASH Program districts (adapted from Giné Garriga and Pérez Foguet (013a)).

The 2010 initiative included a survey that reached 4,925 households across the 21 targeted districts. In each household, service level was captured through a structured questionnaire covering multiple WASH-related issues. Issues included: (*i*) quality of the water source, (*ii*) type of main drinking water source, (*iii*) distance from dwelling to the water source, (*iv*) functionality of water supply in the household, (v) person responsible for dwelling water, (vi) domestic water consumption, (vii) type of sanitation facilities, ($viii$) sanitary inspection of water supplies, and (iv) point-of-use water treatment. The standards (i.e. the minimum levels to be attained in the provision of WASH services) are shown in Table 2.

Table 2: WASH issues considered in the case study.

c_j	Criteria	Standard
c_1	Quality of the water delivered	Water delivered with good analysis results
c_2	Type of main drinking water source	Access to improved drinking water sources
c_3	Distance from dwellings to water source	Time spent in water fetching less than 30 minutes
c_4	Functionality of household water supply	Functioning water supply
c_5	Person responsible for dwelling water	Person responsible not a child
c_6	Domestic water consumption	Water consumption more than 20 liters per capita per day
c_7	Type of sanitation facilities	Access to improved sanitation facilities
c_8	Sanitary inspection of water supplies	No identified risk to contaminate water
c_9	Point-of-use water treatment	Adequate treatment method used at the household

Each household was given a value of 0 or 1 depending on whether it met the standard (1) or not (0). This provided the number of households (x_i) meeting the required standard. The proportion of households that met the standards (p_i) was estimated for each district as x_i/n, being n the total number of households sampled in each district. The survey data is shown in Table 3. This data constituted the performance values for our MCDA models. The alternatives in the decision problem were the rural communities in the 21 districts in rural Kenya, and the criteria the ones shown in Table 2.

Table 1: Summary of studies in water resources management comparing different MCDA models.

MCDA methods compared	**Decision problem**	**Reference**
ELECTRE-III; MAUT; CP	River basin planning: selection of the best alternative for flood control in Tucson Basin (USA)	Duckstein et al. (1982)
MATS-PC; ARIADNE; EXPERT CHOICE; ELECTRE-III	Water resources planning: ranking of water supply project plans in Washington Metropolitan Area (USA)	Goicoechea et al. (1992)
MAUT; PROMETHEE-II; AHP; ELECTRE-III	Water resources management: evaluation of operation alternatives of the Red Bluff Diversion Dam (USA)	Mahmoud and Garcia (2000)
ELECTRE-III; PROMETHEE-II	Strategic natural resources planning: ranking of forest strategies in Kainuu (Finland)	Kangas et al. (2001)
ELECTRE-I; ELECTRE-III; MAUT; AHP; TOPSIS	Flood management: prioritization of flood management alternatives in Golestan (Iran)	Chitsaz and Banihabib (2015)
MAUT; AHP	Rural water supply planning: selection of the best technology for water supply in Bangladesh	Sikder and Salehin (2015)
MAUT; AHP; ELECTRE-III	Water resources strategic management: ranking of flood management alternatives in Shahrood (Iran)	Banihabib et al. (2017)

Table 3: Results of the household survey (n the sample size, x_i the number of households meeting the standard, and p_i the estimated proportion of population meeting the standard).

District	n	c_1		c_2		c_3		c_4		c_5		c_6		c_7		c_8		c_9	
		x_1	p_1	x_2	p_2	x_3	p_3	x_4	p_4	x_5	p_5	x_6	p_6	x_7	p_7	x_8	p_8	x_9	p_9
A1	247	193	0.781	83	0.336	51	0.206	232	0.939	237	0.960	154	0.623	159	0.644	175	0.709	160	0.648
A2	195	167	0.856	9	0.046	159	0.815	176	0.903	194	0.995	169	0.867	169	0.867	105	0.538	134	0.687
A3	186	131	0.704	93	0.500	110	0.591	184	0.989	178	0.957	118	0.634	156	0.839	132	0.710	92	0.495
A4	238	177	0.744	133	0.559	143	0.601	210	0.882	228	0.958	140	0.588	72	0.303	80	0.336	53	0.223
A5	209	107	0.512	61	0.292	106	0.507	173	0.828	203	0.971	83	0.397	27	0.129	75	0.359	60	0.287
A6	230	159	0.691	119	0.517	85	0.370	162	0.704	227	0.987	90	0.391	50	0.217	45	0.196	47	0.204
A7	224	146	0.652	104	0.464	44	0.196	191	0.853	218	0.973	63	0.281	106	0.473	26	0.116	58	0.259
A8	230	188	0.817	25	0.109	20	0.087	230	1.000	223	0.970	120	0.522	149	0.648	125	0.543	108	0.470
A9	429	338	0.788	123	0.287	63	0.147	378	0.881	387	0.902	210	0.490	211	0.492	280	0.653	201	0.469
A10	240	173	0.721	160	0.667	116	0.483	238	0.992	214	0.892	97	0.404	77	0.321	124	0.517	162	0.675
A11	236	191	0.809	101	0.428	4	0.017	157	0.665	207	0.877	114	0.483	57	0.242	157	0.665	22	0.093
A12	218	157	0.720	169	0.775	113	0.518	198	0.908	205	0.940	155	0.711	100	0.459	159	0.729	138	0.633
A13	246	132	0.537	52	0.211	109	0.443	242	0.984	233	0.947	129	0.524	118	0.480	218	0.886	153	0.622
A14	244	205	0.840	130	0.533	74	0.303	226	0.926	219	0.898	150	0.615	161	0.660	176	0.721	140	0.574
A15	242	134	0.554	61	0.252	88	0.364	223	0.921	220	0.909	122	0.504	107	0.442	182	0.752	167	0.690
A16	249	203	0.815	167	0.671	134	0.538	237	0.952	241	0.968	166	0.667	135	0.542	207	0.831	190	0.763
A17	230	190	0.826	199	0.865	97	0.422	124	0.539	227	0.987	114	0.496	108	0.470	95	0.413	87	0.378
A18	128	71	0.555	51	0.398	54	0.422	102	0.797	125	0.977	27	0.211	5	0.039	14	0.109	22	0.172
A19	229	177	0.773	72	0.314	176	0.769	218	0.952	227	0.991	116	0.507	103	0.450	182	0.795	160	0.699
A20	240	195	0.812	41	0.171	60	0.250	224	0.933	233	0.971	63	0.263	70	0.292	89	0.371	16	0.067
A21	235	168	0.715	159	0.677	114	0.485	210	0.894	230	0.979	116	0.494	151	0.643	61	0.260	151	0.643

In the MAUT model, the weights of criteria were determined by a Principal Analysis Component (PCA) following the methodology developed by Nardo et al. (2005). This method has already been used in different WASH-related indices (Giné Garriga and Pérez Foguet 2010, 013b; Pérez-Foguet and Giné-Garriga 2011). It is important to draw attention to the fact that, while in MAUT weights represent the relative importance of criteria, in ELECTRE-III weights express the decision-makers deliberate position regarding the 'voting power' of each criterion (Figueira et al. 2010). Consequently, a study involving the decision-makers of the WASH sector in Kenya would be necessary to assess their positions on the different criteria. Without access to these decision-makers, it was necessary to translate the weights obtained in the MAUT model into indices of importance for ELECTRE-III. In this case we assigned the same set of weights for both models (Table 4).

Table 4: Criteria weights used in both MCDA models (obtained from a Principal Component Analysis).

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9
w_j	0.152	0.160	0.101	0.054	0.148	0.052	0.073	0.112	0.147

4. Results and discussion

4.1. Incorporating data uncertainty in the MCDA models

In order to integrate the uncertainty of the input data into the preference modelling process, we adapted MAUT and ELECTRE-III methodological frameworks as follows.

Model U, based on MAUT theory, starts by building the global utility value of each district $U(a_i)$. To estimate the uncertainty associated to this utility value, the model combines the uncertainty components of the performance values for each criterion $g_j(a_i)$ through an 'uncertainty propagation' method. This allows us to have the districts utility values together with their uncertainties (i.e. the probability distribution of the utility values). Finally, the model conducts a statistical hypothesis test (in this case a Welchs t-test) between each pair of districts to determine their statistical significance. If the null hypothesis of no differences in the utility value means is accepted, the districts are considered to occupy the same ranking position; otherwise, one district ranks higher than the other.

Model S, derived from ELECTRE-III, incorporates data uncertainty in a different manner. Uncertainty of input data is characterized and used to define the discrimination thresholds, according to equations 1-3.

$$q_j = \max |g_j(a)_U - g_j(a)|, |g_j(b)_L - g_j(b)| \tag{1}$$

$$p_j = |g_j(a)_U - g_j(a)| + |g_j(b)_L - g_j(b)| \tag{2}$$

$$v_j = k \cdot p_j \tag{3}$$

being $g_j(a)$ the performance values of alternative a on criterion j, $g_j(a)_U$ and $g_j(a)_L$ the upper and lower limits of its confidence interval, and k the veto/preference ratio ($k = v_j/p_j$). In this case we adapt a ratio of $k = 2$.

The concept behind these equations is simple: if the performance values and their associated uncertainties overlap, it is reasonable to consider them indifferent (indifference threshold q_j). Otherwise, if there is no overlap, one alternative may be preferred over the other (preference threshold p_j). Once the discrimination thresholds are calculated, the model follows ELECTRE-III outranking procedure to obtain the final ranking of districts.

Figure 3 highlights the different ways models U and S integrate data uncertainty. Model S is more straightforward, as data uncertainty is directly included through the discrimination thresholds. In contrast, model U requires more steps to propagate uncertainty and conduct hypothesis testing before obtaining the final ranking.

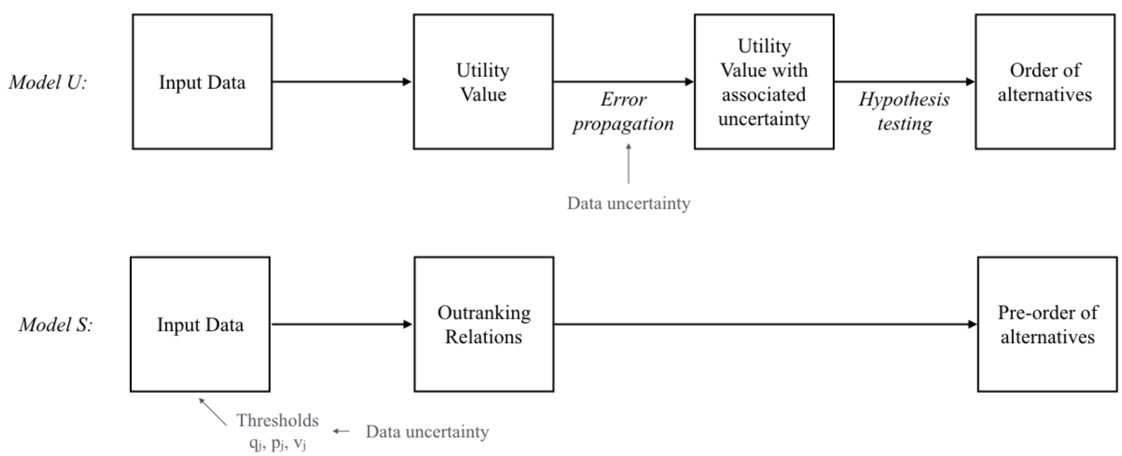


Figure 3: Incorporating data uncertainty in MCDA models: model U based on MAUT theory and model S on ELECTRE-III.

4.2. Characterizing and propagating uncertainty

Uncertainty of input data can be characterized using various methods, both in terms of qualitative and quantitative parameters. In this case, our input data are proportions of populations in each district, estimated from the household surveys. Consequently, data can be considered to follow binomial probability distribution, with parameters n the number of households surveyed and p the proportion of households verifying the criteria (note: we assume that sample sizes n are much smaller than the population size N). To characterize the uncertainty in our data (populations estimates), we use confidence intervals. According to Clopper and Pearson (1934) 'exact' method, the lower and upper limits of the confidence intervals can be expressed as:

$$p_{i_L} = \left[1 + \frac{n - x_i + 1}{x_i \cdot F_{1-\alpha/2,\ 2x_i,\ 2(n-x_i+1)}}\right]^{-1} \tag{4}$$

$$p_{i_U} = \left[1 + \frac{n - x_i}{(x_i + 1) \cdot F_{\alpha/2,\ 2(x_i+1),\ 2(n-x_i)}}\right]^{-1} \tag{5}$$

being $F(c, df_1, df_2)$ the $1-c$ quantile from the F distribution with degrees of freedom df_1 and df_2. Although other methods for calculating the binomial proportion confidence intervals exist, we chose the Clopper-Pearson interval since it was based on the cumulative probabilities of the binomial distribution rather than an approximation to the normal distribution (Agresti and Coull 1998). The confidence intervals are shown in Figure 4.

In model S, these confidence intervals are used to define the indifference, preference and veto thresholds according to equations 1-3, thus providing an easy manner of integrating the data uncertainty in the ranking process.

However, model U requires an uncertainty propagation step in order to determine the uncertainty in the global utility values. We test two error propagation approaches: (*i*) first order, second moment approximation (FOSM), and (*ii*) Monte Carlo simulation (MCS). The first approach uses a Taylor series expansion of the random variable, while the second approach generates artificial samples of input random variables in order to evaluated the distribution of the simulated utility value. Both approaches lead to practically the exact confidence intervals of the global utility values. However, while the FOSM approach only estimates the mean and standard deviation of the utility value, the MCS approach provides its full probability distribution. That is why, although it takes relatively longer time to be completed, we use the MCS approach for hypothesis testing and district ranking.

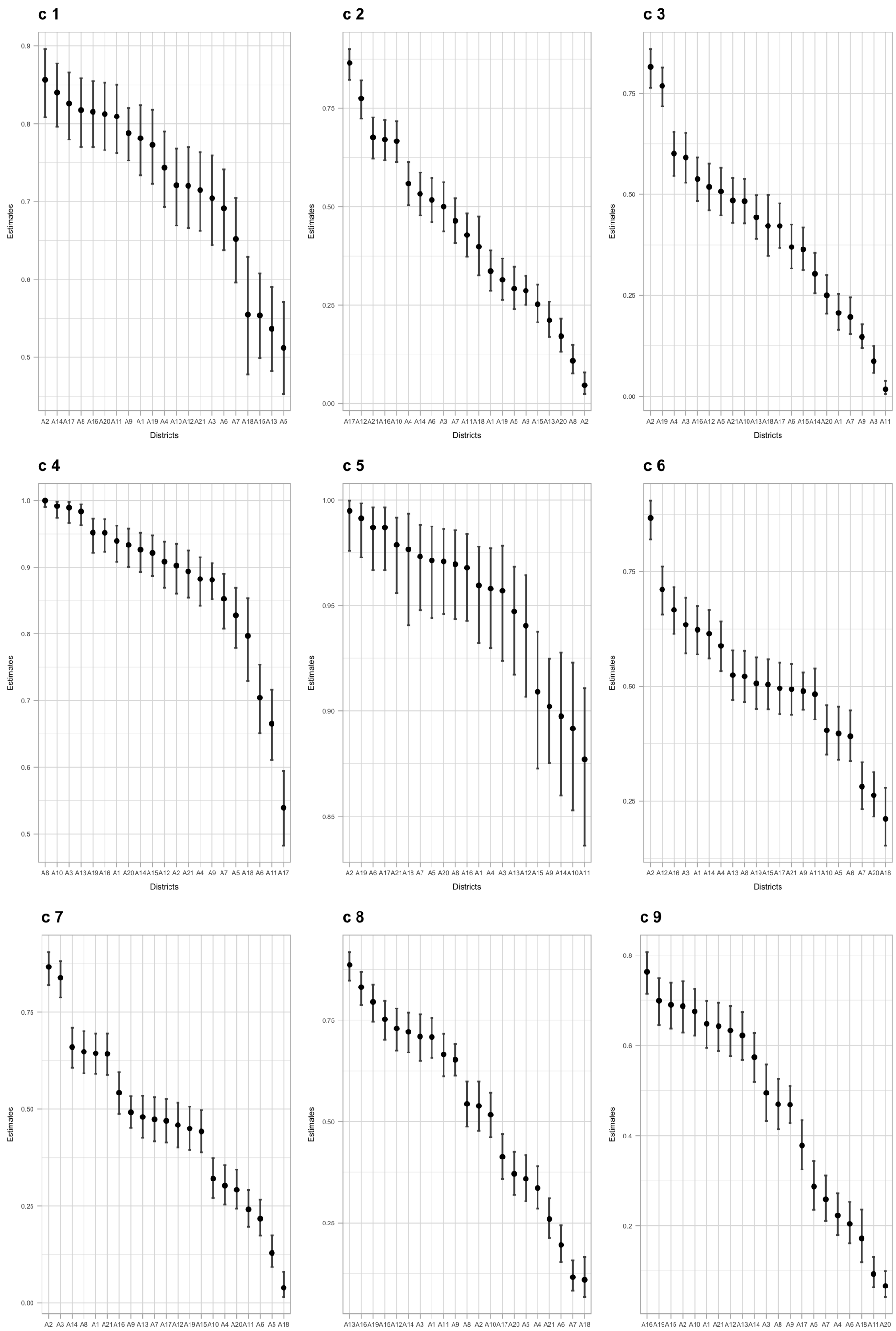


Figure 4: Confidence of intervals of population estimates. (Note: districts are ordered in descending order for each criterion).

4.3. Comparison of rankings

The two MCDA models result in similar district rankings (Figure 5). This convergence between the rankings coincides with results of other studies (Duckstein et al. 1982; Roy and Bouyssou 1986; Goicoechea et al. 1992; Mahmoud and Garcia 2000), where rankings obtained by Weighted Average and ELECTRE-III methods were largely the same.

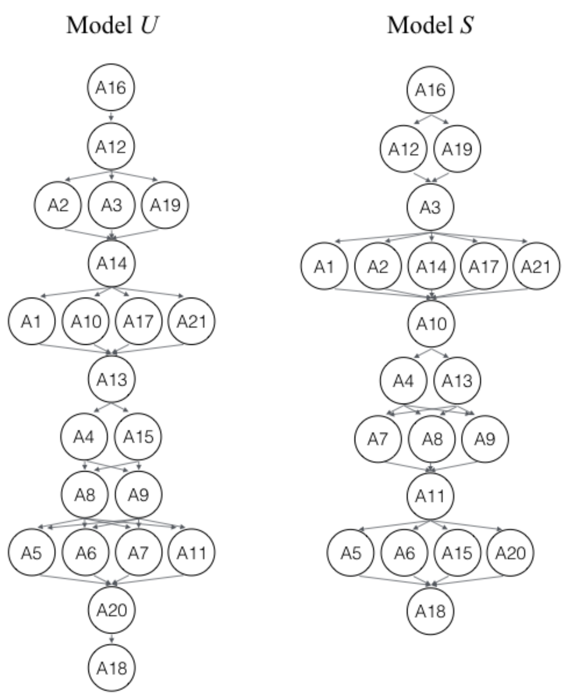


Figure 5: Rankings of the 21 districts obtained with models U and S.

In both cases, districts of Molo (A3), Kisumu (A12), Nyando (A16) and Uasin Gishu (A19) occupy the leading positions. A closer look at the survey data (Table 3) reveals why these four districts had better WASH services than the rest. For instance, in terms of water supply (c_4), more than 95% of their populations had access to functioning water points, 8 percentage points above the national average. The same happens in respect to the distance from dwelling to water (c_3): while on average only 40% of the population had access to a water source in less than 30 minutes, in these four districts the proportion was at least 12 percentage points higher. In addition, more than 71% of households owned latrines in good hygienic conditions (c_8), far from the average of 53%. On the other hand, both models place districts of

Garissa (A5), Isiolo (A6), Mwingi (A18) and Mandera (A20) in the lowest ranks. These four districts severely lacked adequate quantities of water for domestic purposes (c_6): only 21-39% of their populations had access to more than 20 litters of water per capita per day, 30 percentage points below the national average. Furthermore, whereas the access to improved sanitation services was 46% on average (c_7), it did not reach 29% in these districts.

The only major divergence between the two models is the position of districts Tana River (A7) and Kajiado (A15): model U ranks Kajiado higher than Tana River, while model S results in the opposite. This reflects the different principles underlying the two models, especially concerning the compensatory nature of their aggregation procedures. The Kajiado district had better services in terms of distance to the source, functionality of water supplies, domestic water consumption, household water quality and water treatment (c_3, c_4, c_6, c_8 and c_9), but performed poorly in criteria related to improved water sources and person responsible for collecting water (c_2 and c_5). Model U, being fully compensatory, places Kajiado in a higher position because the bad performances on the two criteria are compensated by the rest. On the contrary, model S, which is only partially compensatory, limits this compensation, resulting in a lower position for Kajiado district.

Nonetheless, both models lead to similar targeting and prioritization (Figure 6). These prioritization maps can help understand the inequalities in access to WASH services. In Kenya, there is a serious gap in WASH services in the North-Eastern Province and should thus be targeted in future WASH investments. In the context of limited budgets, this type of targeting and prioritization tools become essential to design the interventions that seek to reduce inequalities in service provision. However, it is particularly important to highlight that, even if the two MCDA models result in different rankings — and hence dissimilar prioritization maps —, both are equally relevant and valid. More important than the selection of which model to apply for WASH planning is to fully understand the mathematical model and principles behind it.

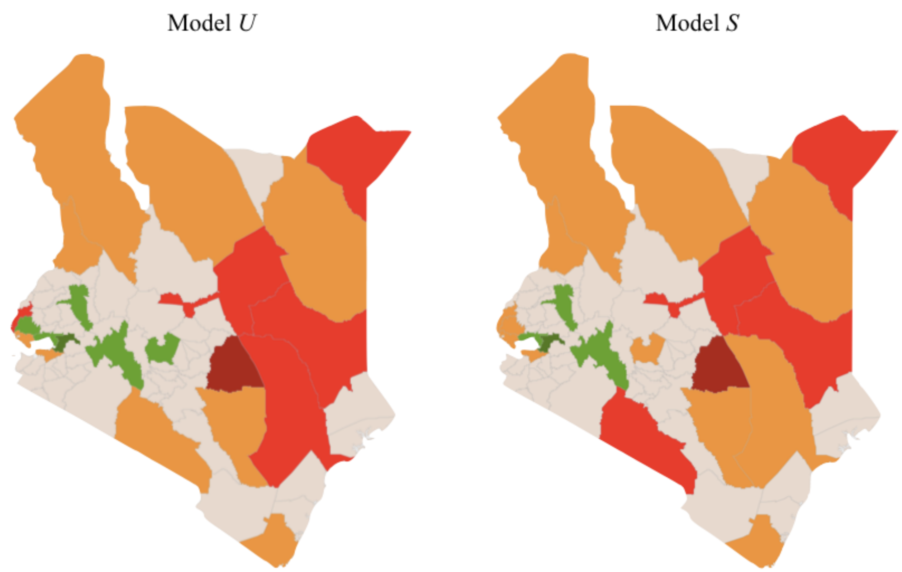


Figure 6: In colour (redorangegreen), prioritization of districts based on their ranking.

5. Conclusions

Safe water supply, sanitation and hygiene (WASH) services are central to meeting global development goals on health, poverty and economic growth. However, strengthening the role of WASH in poverty alleviation requires evidence-based targeting and prioritization instruments in order to identify and focus on those most in need for better WASH services. In this sense, Multi-Criteria Decision Analysis (MCDA) can provide insight on priority-setting and development of WASH interventions, but the task of choosing of the most appropriate model can be challenging. This selection is even more difficult when dealing with uncertainty in the input data, as there is a lack of studies extending MCDA models to integrate data uncertainty.

In this paper, we present and compare two MCDA models, based on MAUT and ELECTRE-III, for targeting and prioritization of WASH services. Unlike other comparisons in the literature, we adapt the MCDA methodological frameworks to address the uncertainty of the input data.

The main conclusions of this comparison are:

- The two models incorporate uncertainty in the input data in a considerable different manner. Model U, based on MAUT, requires a step of 'uncertainty propagation' in order to characterize the uncertainty of global utility values, as well as a step of 'hypothesis testing' to determine the ranking of alternatives. Model S, based on ELECTRE-III, presents a more straight-forward ranking procedure, as data uncertainty is directly included through the discrimination thresholds.

- In the WASH sector, household estimates used for targeting and prioritization purposes are inferred from representative samples from the overall population. Therefore, it is important to characterize the precision of the estimated values. A simple way to express the uncertainty in the estimates, and its effect on the MCDA models output, is through confidence intervals.

- Both models can be useful decision-aid instruments for targeting and prioritization in the WASH sector. In this case study, the two models yield similar rankings and lead to similar prioritization. However, it is noteworthy to remember that MCDA models should not be used to reveal the 'right' prioritization, but to guide the decision analysis process. While the selection of the MCDA model is important, more emphasis should be given on defining the decision problem comprehensively and understanding the theoretical principles underlying each technique.

Conflict of Interest - None

Agresti, A. and Coull, B. A. (1998). Approximate is Better than Exact for Interval Estimation of Binomial Proportions. *The American Statistician*, 52(2):119–126.

Banihabib, M. E., Hashemi-Madani, F.-S., and Forghani, A. (2017). Comparison of Compensatory and non-Compensatory Multi Criteria Decision Making Models in Water Resources Strategic Management. *Water Resources Management*, 31(12):3745–3759.

Chitsaz, N. and Banihabib, M. E. (2015). Comparison of Different Multi Criteria Decision-Making Models in Prioritizing Flood Management Alternatives. *Water Resources Management*, 29(8):2503–2525.

Clopper, C. and Pearson, E. S. (1934). The use of confidence or fiducial limits illustrated in the case of the binomial. *Biometrika*, 26(4):404–413.

Duckstein, L., Gershon, M., and McAniff, R. (1982). Model selection in multiobjective decision making for river basin planning. *Advances in Water Resources*, 5:178–184.

Ezbakhe, F. and Pérez-Foguet, A. (2018). Embracing data uncertainty in water decision-making: an application to evaluate water supply and sewerage in Spain. *Water Science and Technology: Water Supply (In press)*.

Figueira, J. R., Greco, S., Roy, B., and Słowiński, R. (2010). *ELECTRE Methods: Main Features and Recent Developments, in Handbook of Multicriteria Analysis*. Springer, Berlin, Heidelberg.

Giné-Garriga, R., Fernández de Palencia, A., and Pérez-Foguet, A. (2015). Improved monitoring framework for local planning in the water, sanitation and hygiene sector: From data to decision-making. *Science of The Total Environment*, 526:204–214.

Giné-Garriga, R., Jiménez-Fernéndez de Palencia, A., and Pérez-Foguet, A. (2013). Water-sanitation-hygiene mapping: An improved approach for data collection at local level. *Science of the Total Environment*, 463-464:700–711.

Giné Garriga, R. and Pérez Foguet, A. (2010). Improved Method to Calculate a Water Poverty Index at Local Scale. *Journal of Environmental Engineering*, 136(11):1287–1298.

Giné Garriga, R. and Pérez Foguet, A. (2013a). Water, sanitation, hygiene and rural poverty: issues of sector monitoring and the role of aggregated indicators. *Water Policy*, 15(6):1018–1045.

Giné Garriga, R. and Pérez Foguet, A. (2013b). Unravelling the Linkages Between Water, Sanitation, Hygiene and Rural Poverty: The WASH Poverty Index. *Water Resources Management*, 27(5):1501–1515.

Goicoechea, A., Stakhiv, E. Z., and Li, F. (1992). Experimental Evaluation of Multiple Criteria Decision Models for Application to Water Resources Planning. *Journal of the American Water Resources Association*, 28(1):89–102.

Ishizaka, A. and Nemery, P. (2013). *Multi-criteria decision analysis : methods and software.* John Wiley & Sons, Ltd.

Kangas, A., Kangas, J., and Pykäläinen, J. (2001). Outranking methods as tools in strategic natural resources planning. *Silva Fennica*, 35(2):215–227.

Kenya National Bureau of Statistics (2010). Kenya Demographic and Health Survey 2008 - 2009. *KNBS and ORC Macro, Maryland.*

Mahmoud, M. R. and Garcia, L. A. (2000). Comparison of different multicriteria evaluation methods for the Red Bluff diversion dam. *Environmental Modelling & Software*, 2815(5):471–478.

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A., and Giovannini, E. (2005). Handbook on Constructing Composite Indicators. *OECD Publishing.*

Pérez-Foguet, A. and Giné-Garriga, R. (2011). Analyzing Water Poverty in Basins. *Water Resources Management*, 25(14):3595–3612.

Pérez-Foguet, A. and Giné-Garriga, R. (2018). Sampling in surveys with reduced populations: a simplified method for the water, sanitation, and hygiene sector. *Waterlines*, 37(3):177–189.

Roy, B. and Bouyssou, D. (1986). Comparison of two decision-aid models applied to a nuclear power plant siting example. *European Journal of Operational Research*, 25(2):200–215.

Roy, B., Slowinski, R., and Treichel, W. (1992). Multicriteria programming of water supply systems for rural areas. *Water Resources Bulletin,*, 28(1):13–31.

Sikder, A. and Salehin, M. (2015). Multi-criteria decision making methods for rural water supply: a case study from Bangladesh. *Water Policy*, 17(6):1209–1223.

Stewart, T. J. and Losa, F. B. (2003). Towards reconciling outranking and value measurement practice. *European Journal of Operational Research*, 145(3):645–659.

Tsang, S., Kao, B., Yip, K. Y., Ho, W. S., and Lee, S. D. (2011). Decision trees for uncertain data. *Transactions on Knowledge and Data Engineering*, 23(1):64–78.

UN Special Rapporteur on the human right to safe drinking water and sanitation (2011). Report of the Special Rapporteur on the human right to safe drinking water and sanitation, Catarina de Albuquerque. A/HRC/18/33. *New York, UN.*

UN-Water (2018). Sustainable Development Goal 6: Synthesis Report on Water and Sanitation 2018. *New York, UN.*

United Nations (2010). Human rights and access to safe drinking water and sanitation. A/HRC/RES/15/9. *New York, UN.*

WHO and UNICEF (2006). Core questions on drinking water and sanitation for household surveys. *Geneva, UN.*